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T.W. Bickmore
Aerojet Propulsion Division
Sacramento, CA

W.A. Maul
Sverdrup Technology, Inc.
Brookpark, Ohio

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Timothy W. Bickmore
Aerojet Propulsion Division
Sacramento, California

William A. Maul
Sverdrup Technology, Inc.
Lewis Research Center Group
Brookpark, Ohio

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Abstract

A generic software architecture has been developed for post-test diagnostics of rocket engines, and is currently being applied to the post-test analysis of the Space Shuttle Main Engine (SSME). This research specifically deals with one module of the architecture—the Systems Section—which is currently under development by personnel at NASA Lewis Research Center, NASA Marshall Space Flight Center, and Aerojet Propulsion Division. Brief overviews of the manual SSME systems analysis process and the overall SSME diagnostic system architecture are presented. The approach used in the Systems Section is then presented in detail, along with examples validating the case-based reasoning portion's operation on SSME anomalies.

I. Introduction

This research and development effort is a joint project among Aerojet Propulsion Division (APD), the NASA Marshall Space Flight Center (MSFC) and the NASA Lewis Research Center (LeRC), to develop an automated post-test diagnostic system of a working rocket engine, the Space Shuttle Main Engine. The Space Shuttle Main Engine (SSME) is a complex reusable rocket engine that is constantly tested and monitored in order to ensure safety and improve performance. Thorough analysis is performed after each SSME firing based on current understanding of the system operation. These post-test analyses involve time-consuming, repetitive tasks that can be automated to allow system analysts the freedom to spend more time analyzing non-routine engine behavior. A generic software architecture has been developed. One module that has been completed is the SSME High Pressure Oxidizer Turbopump (HPOTP). This module currently detects and diagnoses five failure modes of the HPOTP. The effort currently underway, involving government and industry, will result in a new software module for this architecture—the Systems Section—which will perform system-level automated SSME post-test diagnosis.

This paper describes the current manual data analysis review process; the architecture of the SSME Post Test Diagnostic System (PTDS); the architecture of the Systems Section of the PTDS, which automates the analyses performed by the Systems Group at MSFC; and finally, the Gains Reasoner Module (GRM) which is responsible for identifying SSME anomalies. The GRM uses case-based reasoning to automate the post-test diagnostic process of the system-level SSME data analysts. The gains reasoner module performance was evaluated by analyzing the automated output to three test cases.

II. The SSME Post-Test Diagnostic System

Test firings are currently conducted on test stands A1, A2 and B1 at Stennis Space Center, and on the Technology Test Bed test stand at MSFC. The digitized information from these tests are transferred to teams of data analysts at MSFC. The data is placed in time profile plot packages and disseminated to various specialized analysis groups, including: system-level performance analysis, combustion devices, dynamics and turbomachinery. Each group reviews the plots in order to detect any anomalies in the data. Once an anomaly is discovered, hypotheses about the anomaly's cause are generated and verified by further analyzing the remaining plot information, inspecting past performance of the engine and

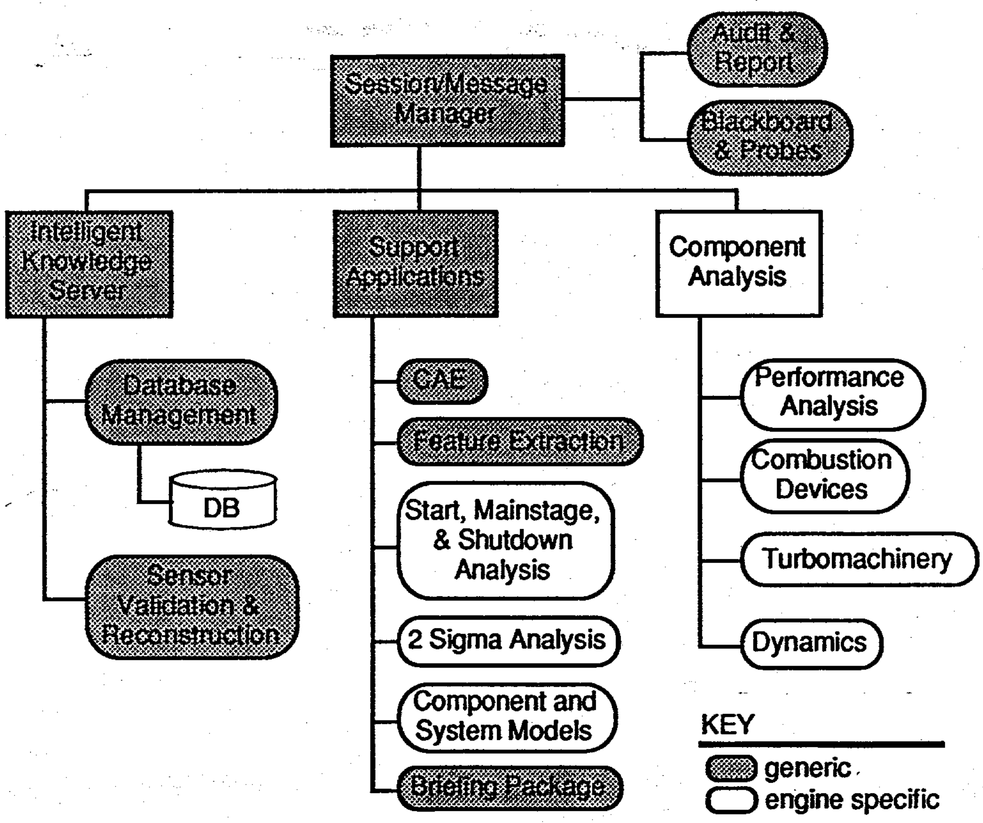

Fig. 1. SSME Post-Test Diagnostic System Architecture[1]

test stand and consulting with other specialized data analysts.

In order to automate this process, specific tasks needed to be defined. Figure 1 illustrates the current view of the SSME PTDS architecture. This architecture includes modules for each of the data analysis groups. The architecture also reflects the generic and engine-specific portions of the PTDS. This architecture allows for modular development, is capable of handling large amounts of information from a variety of data sources and provides a graphical user interface for the data analysts.

III. Overview of the Systems Module

The Systems Data Analysis Group at MSFC is responsible for looking at test data from the entire engine, determining if any anomalies occurred, and if so, isolating the problem to a component and possibly a failure mode. Rather than being experts in a particular component or set of components, such as the Turbomachinery Group, members of the Systems Group are experts in the behavior of the engine as an overall system, and in how components interact with each other.

Sensor data analyzed by the Systems Group is typically plotted against a reference; either data from one or more previous tests (see Figure 2), or composite data representing the mean and standard deviation of a relatively large group of test firing datasets. Significant variations between the current test data and the reference are noted and investigated. Explanations for variations fall into one of the following categories:

- Sensor Failures — Usually the first question pursued by an analyst when an anomaly is found is "is it real?". Plots from related sensors are analyzed to see if they also show a significant shift at the same time as the anomaly. Pre- and post-test data is checked to make sure that the sensor in question is reading the appropriate ambient condition.

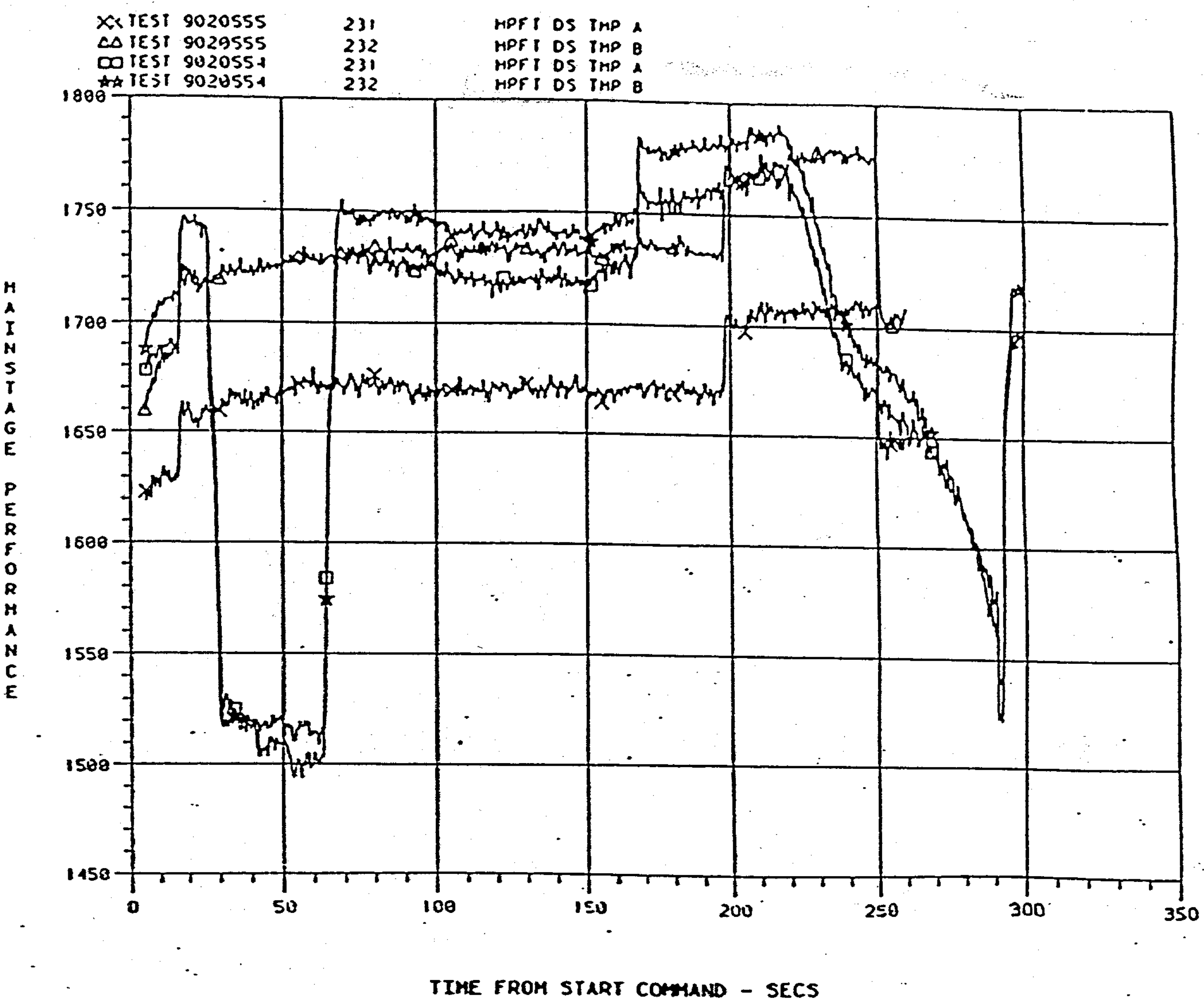

Fig. 2. Example SSME Data Plot (High Pressure Fuel Turbine Discharge Temperature Measurements on Tests 902554 and 902555)

- Hardware Changes — Anomalies which manifest themselves as constant offsets may be attributed to differences between the characteristics of the engine under test and the reference engine. Turbopump efficiencies, line resistances, injector efficiencies and other characteristics can all vary enough from engine to engine and test to test (due to many line-replaceable units) to cause a significant change in operating characteristics which show up as variations on the data plots.

- External Effects — Systems Analysts will determine if the anomaly can be attributed to influences which are external to the engine. External effects include changes in commanded power level, pressurization or venting of the propellant tanks, transfer of propellant from a barge into the propellant tanks (causing a change in inlet temperature), or changes in the propellant pressurization flows.

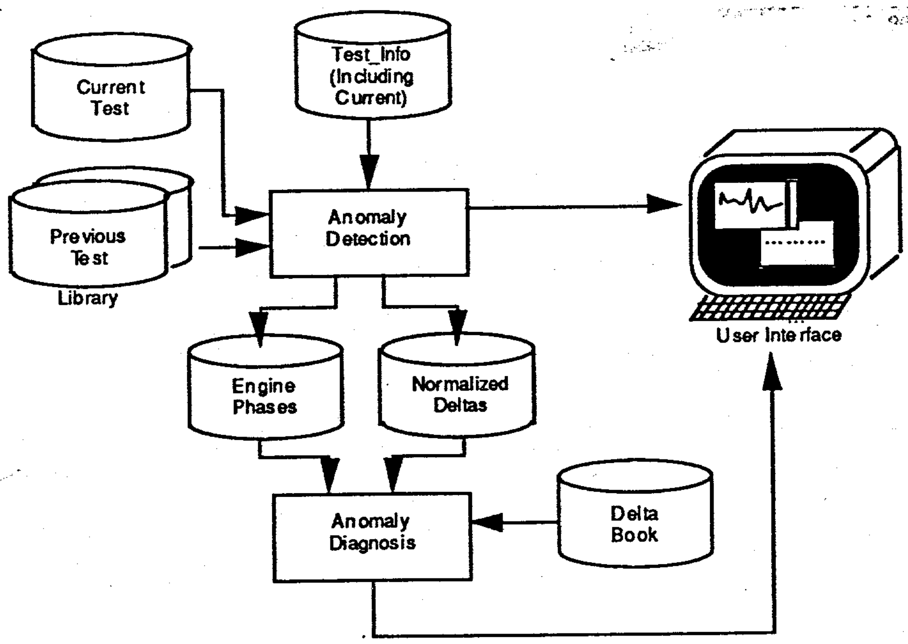

Fig. 3. Systems Section Architecture

- Failure Mode — Finally, if none of the above effects can explain the anomaly, the analyst must assume that something in the engine itself, such as a component failure, has caused the discrepancy.

The objective of the Systems Section of the SSME Post-Test Diagnostic System is to automate as much of the anomaly detection and diagnosis capability of the Systems Analysts as possible.

The Systems Section software is being implemented using the CLIPS expert system shell, the C programming language, the Ingres relational database, and the Motif graphical user interface on Sun SPARCstations.

IV. Systems Module Architecture

To help ensure acceptance of the system by the users, we are attempting to emulate the various diagnostic strategies currently used by the Systems Group as accurately as possible. Thus, the software architecture of the Systems Section is partitioned into modules which perform the anomaly detection and categorization steps described above. Figure 3 shows the top-level architecture of the Systems Section. At this level the system can be broken into two major functions: Anomaly Detection and Anomaly Diagnosis. These functions are described in the subsequent sections.

IV.1. Anomaly Detection

Figure 4 shows a more detailed look at the Anomaly Detection module of the Systems Section.

Data from the current test is first run through a series of feature detection algorithms, which detect level shifts, spikes, peaks, and other features in selected sensor traces. These features are used by various routines in the Systems Section software, to detect changes in engine operational state, sensor failures, and anomalies. One of the most important classes of features extracted is the set of differences between the current test and a comparison test, which become the basis for anomaly diagnosis once the explainable effects have been filtered out.

The Engine Phase Reporter examines the features for the current test and determines the quasi-steady-state intervals which will be used to partition the data.

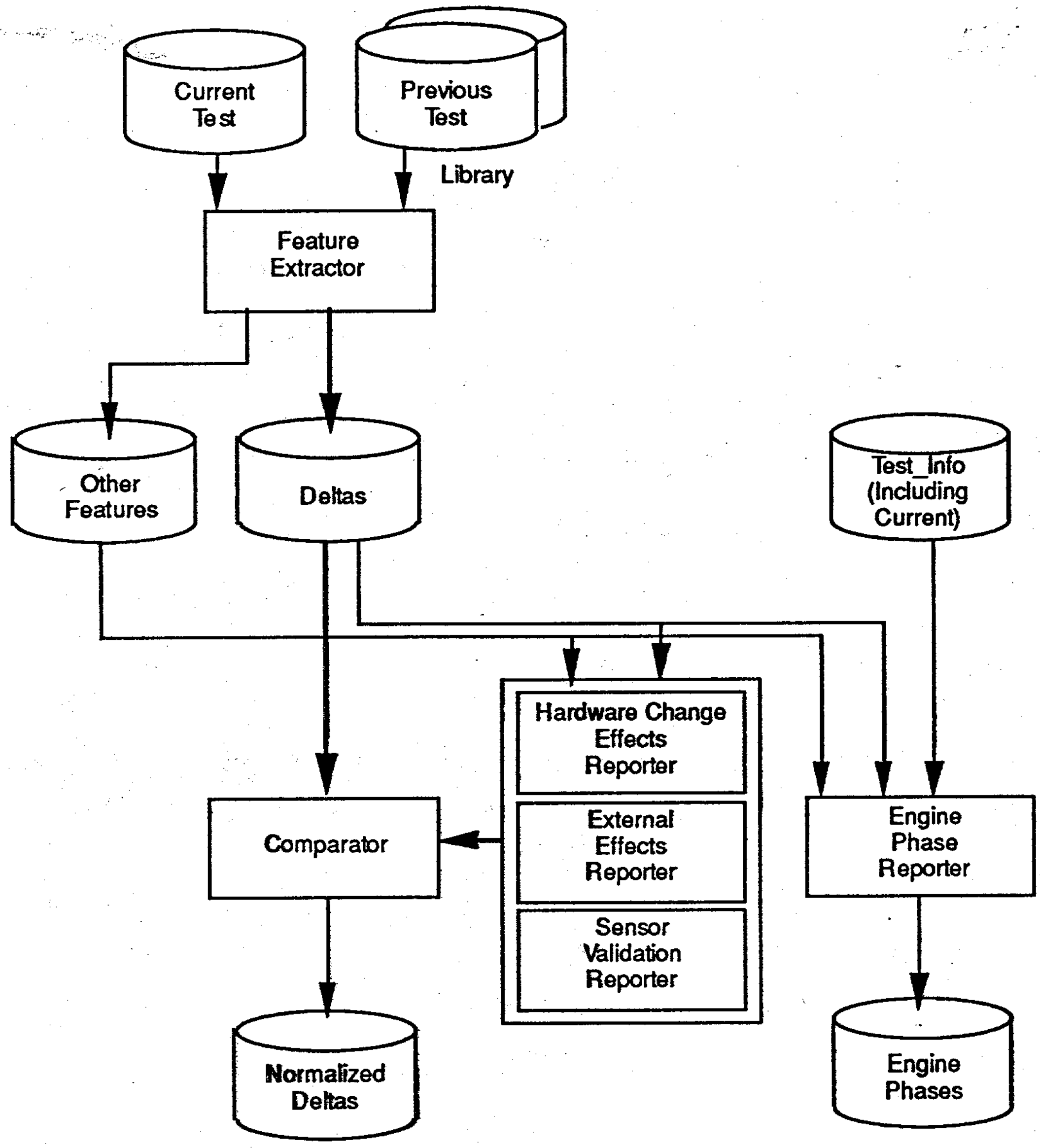

Fig. 4. Anomaly Detection Module Architecture

The Hardware Change Reporter anticipates differences between the current test and the comparison test(s) due to changes in engine hardware, and outputs these differences to the Comparator. A good example of the kind of information used by these routines are differences in efficiencies between high pressure pumps which can significantly alter the operation of the engine.

The Sensor Validation Reporter examines sensor data from the current test to detect failed sensors. As the analysts do, these routines will employ pre- and post-test ambient checks, and related sensor value checks as strategies for detecting sensor failures. Failed sensors are flagged so their values are not used by other modules in the system.

The External Effects Reporter takes information about the test, such as the scheduled power level profile and propellant pressurization and venting schedules, and features from the test dataset under analysis, and determines expected changes in sensor data due to changes in engine operation influenced by externally controlled events.

Finally, the Comparator acts as a filter which takes the difference between the current test and the comparison test(s), and removes those differences which could be "explained" by either hardware differences, sensor failures, or external effects. What is left is a set of "true" anomalies which must be explained by the Anomaly Diagnosis module.

IV.2. Anomaly Diagnosis

Once anomalous features have been detected in a set of performance parameters, and these features cannot be filtered by the specialized diagnostic routines in the Anomaly Detection module, then this information is passed on to the GRM. This module attempts to generate probable hypotheses which would explain the current set of parameter gains or shifts. The module has two principle components: a hypothesis database and a case-based reasoner.

The hypothesis database contains information about known system anomalies, including expected gains for the set of performance parameters affected by each anomaly. This information is kept in a data structure which includes the type of anomaly, the SSME's response to the anomaly and the relative magnitudes of both the anomaly and the responses. Each data structure is called a hypothesis case. This information was generated by exercising a quantitative system performance model of the SSME and consulting with system-level domain experts.

The case-based reasoner is a collection of rules which compare each anomaly response pattern in the hypothesis database to the normalized deltas for the engine under analysis in order to select a small set of most probable cases. To perform this selection, the case-based reasoner employs two comparison techniques: a sign or direction comparison and a minimum distance comparison.

The first technique compares the directions of the observed gains with the directions of the gains expected for each hypothesis case. A score is generated for each observed gain and accumulated for a total case score. Table 1 defines the types of results currently available, along with the score for each type. The accumulated score is used to rank the hypothesis cases for further evaluation. This provides an initial screening of the hypothesis case database. This screening reduces the processing time, by reducing the number of cases which undergo the computationally more intensive minimum distance evaluation.

Type	Description	Score
Match	Case Gain Matches Observed Gain	0
Not Covered	Observed Gain Not In Case Fact	1
Not Observed	Case Gain Not Observed	100/K
Opposite	Case Gain Opposite In Direction To Observed Gain	1000/K

Table 1. Direction Comparison Types. The variable K found in the Score column is equal to the number of parameter shifts in the particular case being evaluated.

The minimum distance comparison technique is applied to the hypothesis cases selected by the sign comparison technique. The hypothesis cases and the observed parameter set can be treated as points in N-space, where N is the number of observed parameters in the rocket engine. Hypothesis case vectors are vectors from the origin through each hypothesis case point. These vectors represent linear extrapolations of each respective case. The length of the line segment perpendicular to a case vector, and with endpoints on the case vector and at the observed parameter set, is the minimum distance for that case. The minimum distance is used to rank each hypothesis case.

The projection of the observed case line, a line from the origin to the observed parameter set, on the hypothesis case vector is used to compute a scaling factor for the hypothesis case. This scaling capability allows the hypothesis database to be of manageable size; without it, multiple versions of each hypothesis case would need to be kept (e.g., 10 different magnitudes of leaks in the main combustion chamber cooling circuit). This scaling has been empirically justified by data analysts who routinely assume that gains models are linear and additive.

Additional rules could be activated at this stage to further refine the hypothesis cases. If for example, the scaling of the cases indicates that case A, a change in turbine efficiency, is a 50% change and physically that size of change is impossible, then either case A can be eliminated from the probable hypothesis case subset or the minimum distance for case A could be reevaluated with the scaling factor restricted to the maximum efficiency change. These rules would need to be heuristically generated.

IV.3. Validation

In order to validate the case-based reasoner, three example failure scenarios were generated and passed through the module. Each test scenario consisted of a set of gains, generated to match or partially match a hypothesis case. In each verification test the case-based reasoner module properly identified the most probable hypotheses. Tables 2 through 4 show the results for each test scenario. The tables include the five top selected cases from the sign comparison, the overall ranking of the cases based on the minimum distance, and the scaling factor of the hypothesis case based on the observed gains.

The first test scenario was designed to match exactly with the hypothesis case, Main Combustion Chamber Pressure (MCC PC) Biased High. This hypothesis case was based on the SSME's response to a sensor bias in a controlled parameter; one of four MCC PC channels was biased 20 psi high. In this test case, the case-based reasoner returns a perfect match and a minimum distance of zero for this hypothesis case. In addition, the case-based reasoner returns several other cases, each ranked below the preferred hypothesis.

The second test scenario was designed to demonstrate the partial matching capabilities of the case-based reasoner. A set of gains was selected which matched the LPOT flowrate increase hypothesis case, except an additional parameter gain was added. The LPOT flowrate increase case ranked highest among the selected hypotheses. The second, third and fourth-ranked hypotheses did not include two of the observations and had an expected gain that was not observed in the input set. Both the sign-match and minimum distance scores for these cases were very close to each other. The fifth-ranked case had only a single expected gain that was in the input set. Although the sign score for this case was high, the minimum distance dropped its ranking to fifth.

The third scenario was designed to evaluate the scaling capability of the case-based reasoner. The input gains were based upon a 1/2 multiple of the hypothesis case MCC Coolant Leak. This scenario was generated from the SSME's response to a 3 lb/s leak on the main combustion chamber's cooling circuit. The result of the case-based reasoning was to rank this hypothesis case with a scaling factor of 1/2, with a minimum distance of zero.

V. Summary

The primary objectives of the SSME system-level post-test diagnostic system are to automate the data analysis and diagnostic process currently performed by the SSME domain experts and to develop a generic approach to the automated diagnosis of liquid fueled rocket engines. The gains reasoner module accommodates these objectives. It automates the diagnostic analysis of specific SSME anomaly cases with generic rules that could be applied to any system. This module performs a mathematical comparison of expected hypothesis direction and magnitude of observed parameter gains. The module is also capable of scaling hypothesis facts in order to determine the probable size of the anomaly based upon the observed conditions.

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References

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Selected Cases	Sign Score	Sign Rank	Distance Score	Overall Rank	Scaling Factor
MCC PC Biased High	0.0	1	0.0	1	1.00
Primary Piston Ring Leakage Decrease	6.0	4	4.76	2	1.48
MCC Combustion Efficiency Decrease	45.8	2	5.09	3	1.73
PBP Efficiency Increase	53.0	3	5.12	4	1.24
LPOT Flowrate Decrease	44.0	5	5.43	5	0.01

Table 2. Test Case 1. For this test case, the observed gains provide an exact unscaled match of the MCC PC Biased High hypothesis case.

Selected Cases	Sign Score	Sign Rank	Distance Score	Overall Rank	Scaling Factor
LPOT Flowrate Increase	1.0	1	2.71	1	1.0
LOX Inlet Temperature Increase	22.0	3	33.73	2	0.43
HPOP Discharge Resistance Increase 1	22.0	3	33.77	3	0.50
Primary Piston Ring Leakage Increase	22.0	3	33.85	4	1.15
PBP Efficiency Decrease	5.0	2	34.11	5	1.50

Table 3. Test Case 2. For this test case, the partial matching capability of the case-based reasoner is demonstrated.

Selected Cases	Sign Score	Sign Rank	Distance Score	Overall Rank	Scaling Factor
MCC Coolant Leak	0.0	1	0.00	1	0.50
LPFT Efficiency Decrease	7.0	4	4.73	2	0.88
Primary Piston Ring Leakage Increase	6.0	2	11.40	3	1.06
Nozzle Coolant Leak	6.0	2	11.54	4	0.30
PBP Efficiency Decrease	10.0	5	12.14	5	1.12

Table 4. Test Case 3. For this test case, the observed gains were selected for 1/2 scaled match of the MCC Coolant Leak hypothesis case.